SPE-196064-MS

AI-Derived Logs for Formation Evaluation Using Case Studies in the Gulf of Mexico and Trinidad & Tobago

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This paper was prepared for presentation at the SPE Annual Technical Conference and Exhibition held in Calgary, Alberta, Canada, 30 Sep - 2 October 2019.

Abstract

Borehole-log data acquisition accounts for a significant proportion of exploration, appraisal and field development costs. As part of Shell's technical competitive scoping, there is an ambition to increase formation evaluation value of information by leveraging drilling and mudlogging data, which is traditionally used in petrophysical or reservoir modelling workflows.

Data acquisition and formation evaluation for the shallow-hole sections (or overburden) are often incomplete. Logging-while-drilling (LWD) and/or wireline log data coverage is mostly restricted to Gamma Ray (GR), Resistivity (RES) and mud log information and the quality of the logs varies depending on the vendor companies or year of acquisition. In addition, reservoir characterization logs typically cover only the final few hundred to a few thousand feet of the wellbore thus preventing a full quantitative petrophysical, geomechanical, geological correlation and geophysical modelling analysis, which results in a limited understanding of the overburden in the drilled locations and geohazard risk assessment and mitigation.

The use of neural networks (NN) to predict logs is well-known in Petrophysics and has been in use for more than ten years. However, these NN models seldom utilize the drilling and mudlogging data (due to lack of calibration and inconsistency) and until recently they were restricted to the prediction of a synthetic log or to infill gaps in a log. The collaboration between Shell and Quantico has resulted in the development of a plug-in based on a novel artificial intelligence (AI) workflow to generate synthetic/AI logs using log data, drilling dynamics data and mudlogging data from offset wells. The technology is called QLog and the QLog workflow has been successfully evaluated in Shell's offshore fields in Trinidad & Tobago and the Gulf of Mexico.

The results of this study indicate the NN model provides data comparable to that obtained from conventional logging tools over the study area. In fact, when comparing the resulting synthetic logs with the measured logs, *the range of variance is within the expected variance of repeat runs of a conventional logging tool.* Crossplots of synthetic versus measured logs indicate a high density of points centralized about the one-to-one line, indicating a robust model with no systematic biases. The QLog approach provides

several potential benefits. These include a common framework for producing compressional sonic (DTC), shear sonic (DTS), Neutron Porosity (NPHI) and Bulk Density (RHOB) logs in one pass from a standard set of drilling, LWD and survey parameters. Since this framework ties together drilling, formation evaluation and geophysical data, the AI enhances and possibly enables other petrophysical/QI/rock property analysis that includes seismic inversion, high resolution log generation, log QC/editing, real-time LWD, drilling optimization and others.

Introduction

Borehole-log data acquisition accounts for a significant proportion of exploration, appraisal and field development costs. However, wireline and/or LWD logs are often not available for one or more curves for reasons such as operational decisions, tool failure, or environmental risk. In addition to these limitations, reservoir characterization logs typically cover only the final few hundred to few thousand feet of the wellbore. This lack of coverage prevents a full quantitative petrophysical, geomechanical and geophysical modelling analysis as well as geological correlations. These factors result in a limited understanding of the geohazard and geomechanical risk assessment of the overburden sections. For these situations, there is a desire to extract more value of information from the drilling and mud logging data to generate AI logs such as DTC, DTS, RHOB and NPHI via supervised ANN modeling.

A simple AI structure using an ANN can be described as comprising several processing elements, or nodes, that are usually defined in layers: input, output and hidden layers. ANN's have been used in Petrophysics for decades and several published articles have described the structure and operation of AI in the early 1990's (e.g. Hecht-Nielsen 1990; Maren et al. 1990; Zurada 1992; Fausett 1994; Ripley 1996). Following a decline in the use of AI in the early 2000's, AI adoption by the oil industry especially for drilling and reservoir characterization has grown significantly during the past decade.

A review of the literature reveals several studies that have used neural networks to predict petrophysical logs from MWD and wireline logs, (Bhatt, 2002); predict density, resistivity and neutron using wells logs and survey data, (Rolon et al 2005, Rolon et al 2009); create synthetic neutron logs using well log data, (Ghavami, 2011); create synthetic sonic logs from well log data, (Guan, 2012); develop synthetic geomechanical logs (Eshkalak et al. 2013, 2014); and create photoelectric absorption factor (PEF) and unconfined compressive strength (UCS) using wireline logs, (Akinnikawe et al., 2018). However, this entire body of work uses well log data and does not leverage drilling data. Based on our knowledge, there is a limited number of published studies that use ANN models based on drilling data to generate petrophysical or geomechanical logs. For example, there are a few studies that discuss the conversion of drilling data into logs, such as predicting UCS from drilling rate and weight on bit (Hareland et al. 2010 and Kerkar et al., 2014), or also predicting porosity, permeability, Poisson's ratio and rock strength (Cedola et al. 2017 and Tahmeen et al. 2017). However, these only predict geomechanical logs not petrophysical logs. Both Lehman et al. 2016 and Scanlan et al. 2018 discussed a methodology similar to the one that is being described by the current paper to predict petrophysical logs and their application for onshore unconventional and conventional reservoirs.

What is Machine Learning (ML) vs Artificial Intelligence (AI)?

Artificial Intelligence refers to a system that is not natural and has the ability to understand, learn or think. Machine Learning (ML) is a subset of AI that uses algorithms and statistical models to process data to execute a specific task relying on learned data and patterns. Artificial Neural Networks (ANNs) are a type of machine learning that could use supervised learning, unsupervised learning or reinforcement (or graded) learning to perform a task similar to the way a human brain would. In supervised machine learning, the training set is composed of inputs "p" with a corresponding set of targets "t". The inputs are applied to the Neural Network (NN) to generate outputs that are compared to the targets. Learning rules are applied to the

NN to adjust the weights and biases to move the outputs closer to the targets. Reinforcement learning is similar to supervised learning, only the neural network is provided a grade (or score) after some sequence of inputs is applied. This grade is used to adjust the weights and biases of the NN. Unsupervised learning adjusts the weights and biases based only on the inputs, where an output is not generally available. This is often used for clustering applications. The architecture of a neural network defines the relationship between inputs and outputs. There are many types of neural networks such as feedforward neural networks, convolutional neural networks and recurrent neural networks. Feedforward neural networks are essentially a network that connects inputs to outputs using multiple layers in one pass with no backward connection. Convolutional neural networks, and deep neural networks in general, are routinely used for image classification, where initial layers are used to identify initial features, edges and corners, followed by subsequent layers until the final layer that determines if the picture is, for example, a depiction of a cat or a dog. The architecture is organized to retrieve 2D information from images. Recurrent neural networks have feedback connections. They can exhibit temporal behavior, which can be applied to document translation and voice recognition. Due to the nature of the LWD/wireline logs and their relationship with Gamma Ray (GR) and drilling data, feedforward neural networks can be used to predict petrophysical logs. Figure 1 shows an example of a feedforward neural network with one hidden layer and one output layer. The weights and biases in each layer are adjusted while in training.

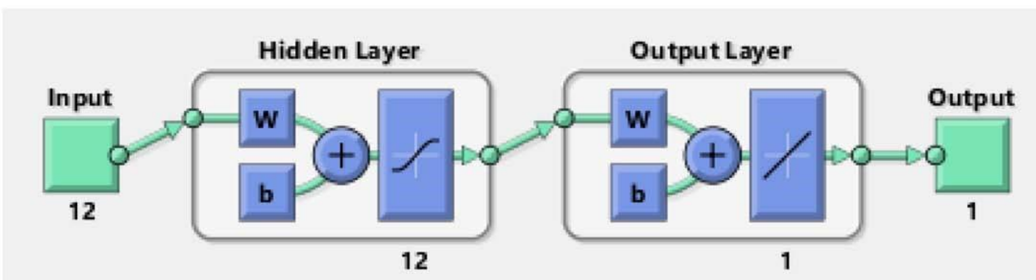

Figure 1—Feedforward neural network example

Description of the AI method used in this study

The particular AI log generation method described in this paper is a commercially available method that has been developed over the last 6 years and has been utilized on both onshore and offshore environments with certain applications having been patented. Certain land applications where the method was previously used are described in Parshall 2015, Scanlan et al. 2018 and Lehman et al. 2016.

This ML approach utilizes an ANN to generate advanced formation evaluation logs (such as DTC, DTS, RHOB and NPHI) from a collection of measurements including the wellbore survey, Gamma, Resistivity (RES), and drilling dynamics such as Rate of Penetration (ROP) and Weight-on-Bit (WOB), etc. Figure 2 show an example of such data. During ANN model creation, the measured logs corresponding to the AI logs to be simulated are also required; these can be obtained from offset wells.

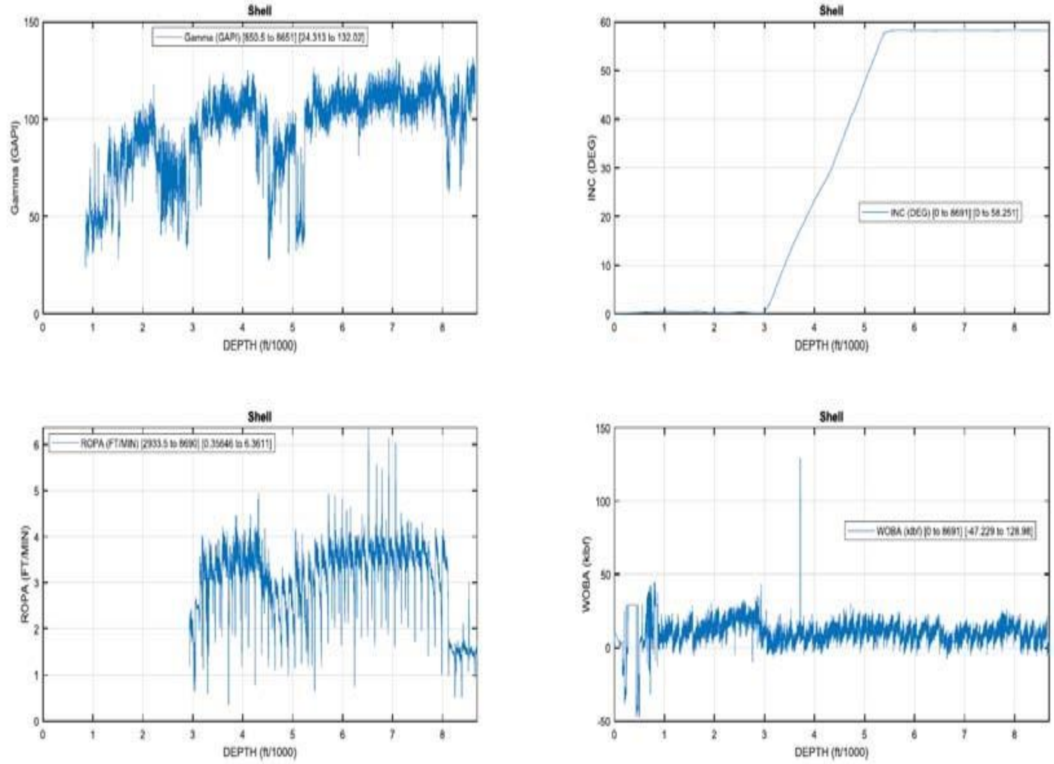

Figure 2—Figures show Gamma ray, inclination, ROP and WOB as example of logs and drilling data

A major strength of this method compared to others is that it makes it possible to generate advanced formation evaluation logs using the drilling dynamics data and Gamma/Res data that are routinely collected on most wells. Additionally, the formation evaluation information content of the drilling dynamics data is fully incorporated to augment the limited content of Gamma/Res logs.

The process to generate the desired formation evaluation logs comprises two main steps, namely the ANN Model Creation phase (building and training) and the ANN Model Operation phase (log simulations for a test well). In the training phase, a model is built using selected data from a group of offset wells in the target area. That model embodies the relationship between input and output data to the model; the input data to the model are the drilling data, together with the Gamma/Res logs along with the survey data, and the output data are the measured logs. In the simulation phase a pre-existing model is used to generate the logs for the test well of interest. Figure 3 conceptualizes the generation of logs using a ML-based calculation engine and a pre-existing model. More details are given for each phase in what follows.

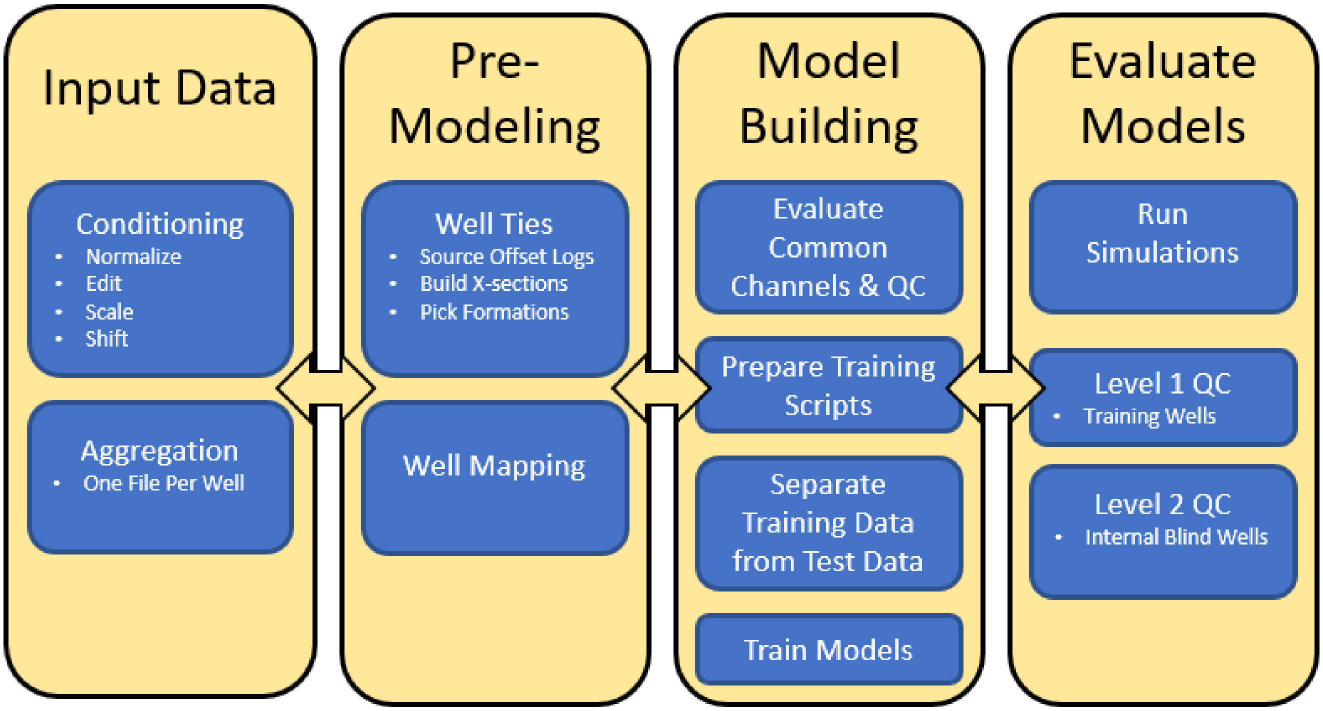

Figure 3—AI log generation workflow

Model creation (Building and Training)

The first phase in the process resulting in the generation of AI logs in a new geographical area is the creation of a model, or preferably of a series of models. Generating several models often proves useful to account for cases such as missing drilling data channels in the test well during the Operation phase.

A model is generated from several selected wells, together with selected input channels. As a result, a series of models or sub-models can be created with similar wells in training but different combinations of input variables. Further, sub-model variations can also be used where similar wells are used but with different depth ranges, or similar input channels but with differences on the modalities they are treated within the NN algorithm (e.g. with or without removal of outliers, or forcing a parameter to be used or not, etc.). There are several key steps followed in the model creation process:

1. Definition of the geological context
2. Data inventory/data coverage
3. Data conditioning and QC for the model building; this includes both the petrophysical logs and the drilling data.
   a. Wells used in training
   b. Wells retained as internal blind tests to validate the results
   c. Model building and training
   d. Model validation
4. Building the Model(s)

In what follows we'll examine some of these steps in more detail. In practice, a minimum number of wells (perhaps 6 to 8, see below) is required for model creation in the targeted area.

1. Definition of the geological context

Model creation starts by assessing the geological context and gathering available data, including the drilling data and the existing measured logs for all the wells available. In theory, the number of wells necessary varies depending on the geological complexity, log characteristics, depositional environment, the aerial extent, the depth range to cover, and the amount of data available for each well. A successful model is based on an appropriate sampling of the various scenarios characterizing the field.

2. Data inventory/data coverage

An important step in model building is to understand the span of data available in order to be able to answer questions such as: how many wells have data, is the data usable as is or after QC conditioning, are all necessary measured channels available, is the entire depth range covered, are the various geological entities to be modeled measured, is there enough coverage of the drilling data, etc.?

The initial effort of data cataloging and definition of available coverage helps in selecting the wells to use in training (how many wells and what combination of wells). The effort continues after data conditioning and QC, iterating as the data sets are built, and as new data or corrected data becomes available.

3. Data conditioning and QC

One of the main tasks that needs to be performed upfront is the gathering of the various data files and the selection of appropriate data.

Usually the measured data is created with different formats and can contain errors, missing values or other inaccuracies. Data channels can be duplicated. Some channels may be misaligned with others. Some parameters can be measured or processed in different ways and recorded on several channels on the same file or on separate files. Data conditioning therefore needs to address these issues in order to end up with quality input data. Here are some common operations performed:

- Normalization (common on Gamma ray data)
- Resampling
- Time-based to depth-based conversion of drilling data, as necessary
- Editing
- Scaling
- Depth shifting
- Merging/splicing and aggregation (concatenation)

Additional data QC may be required, especially for log curves to be used in training, to ensure that the models are trained on valid data.

Following the data conditioning effort, a single set of input and output data is generated for each well. This set of data is ready to be used either in model training or simulation against an existing model.

4. Building the model(s)

Once the number and combinations of wells to use, the depth range to include for each well, and the set of input data to specify are chosen, proprietary software is used to run the ML algorithm to generate the models.

Every model consists of a one or more multilayer neural networks using the wellbore survey, Gamma, Resistivity (RES), drilling dynamics and mud logs as input data. The selection of the number of channels to use as input and details on how to condition them is based on the user's experience and needs to appropriately capture the underlying physics of the drilling process in order to build a successful model. Each model can be set up to predict sonic, density or/and neutron logs – all are modeled independently. The models can be configured to use either all available inputs or a subset of the input data. The subset of inputs allows the person building the model to check the relevance of specific inputs in a given geographic area. For example, models could be created with and without a Resistivity input channel. The final process could determine that the use of Resistivity improves the final results. Also, a model without Resistivity will be useful if the Resistivity log is not available in all wells, or if the sensor has no valid data at specific depths.

Training of the NN is done by applying the selected inputs $\boldsymbol{p_q}$ to the neural network and obtaining a number of outputs $\boldsymbol{a_q}$. For each input $\boldsymbol{p_q}$ is the corresponding target output $\boldsymbol{t_q}$, which we can use to calculate the mean squared error:

$$\widehat{F}(x) = (t(k) - a(k))^2 = e^2(k) \tag{1}$$

where the expectation of the squared error has been replaced by the squared error at iteration k. Different algorithms are used to adjust the weights and biases of the Neural Networks in order to minimize the mean square error. The simplest algorithm is the Least Mean Squares (LMS) algorithm, which was generalized by the Backpropagation algorithm, then improved by the conjugate gradient algorithm and the Levenberg-Marquardt algorithm. The reader could find more detail analysis in the Neural Network Design book by Hagan et al., 2014.

Training of each neural network is executed until one of the following conditions occurs: a predetermined number of iterations is executed or the error in a validation set increases for several iterations.

Result Validation:

Once the models are created, it is important to test them against existing data to verify how well they performed. To do so, a 2-step method is typically used:

- Validation level 1: Verification that the AI logs simulated for wells in training are a good match with the measured data
- Validation level 2: Use of internal and external blind wells, i.e. wells that were purposely excluded from training to be used in this phase – we also expect a good match between simulations and measurements

Internal blind vs. external blind wells – in commercial applications when the model building and AI log calculation are performed by a Service Company for an Operator, it is common to use an external blind test, where the Operator has the measured logs available but provides them to the Service Company only after the simulation results are generated, for validation purposes. So it is not uncommon to develop a model using first an internal blind and then add that well to the training deck for a more robust model before comparing to an external blind test.

In all cases presented in this paper, the goodness of fit between the AI log and its measured counterpart is quantified using the Normalized Root Mean Squared Error (NRMSE) defined in equation (1).

$$\mathrm{NRMSE} = 100\frac{\sqrt{\frac{1}{N}\sum_1^N (X(i) - Y(i))^2}}{\frac{1}{N}\sum_1^N X(ni)} \tag{1}$$

where X is the measured channel, Y is the AI log, N is the number of samples, and NRMSE is expressed as a percentage. Within this framework, it is expected in our experience that simulated density will agree with logging tool density within 2 to 3%, and compressional and shear slowness will agree within 4 to 7%. These values are therefore used as criteria to validate the performance of a model for a level 2 validation test (blind well). A tighter match (smaller NRMSE values) is however expected at level 1 (well in training).

Cases where a poor agreement is observed, especially at level 1, need to be re-examined to make sure that the physics is correctly captured by the model and that all data is appropriately reviewed and corrected.

Generating AI logs for a test well

The model building phase is heavily user-driven. The simulation phase lends itself more easily to automation and can be integrated in a desktop–based or cloud software platform such as that discussed later in this paper.

There are several key steps to generate AI logs:

1. Verification of compatibility of the geological context with existing model(s)

2. Data conditioning and QC for the test wells, i.e. the wells to be simulated; this typically includes the drilling data and LWD Gamma/Res only, as the advanced petrophysical logs are not available.

3. Model selection – selecting a model when a series of models is available:

    a. Based on spatial location and geological context
    b. Based on input data range. In order to produce reliable results, the range of the input data must be covered by the data in training. If one or more input channels is Out of Range (OOR), adjustments should be made, such as selecting a different model that does not use the channel(s) that is (are) OOR. Figure 4 shows a case where the ROP is partly OOR.

4. Run the calculation engine run on the test well to generate the simulated output petrophysical logs

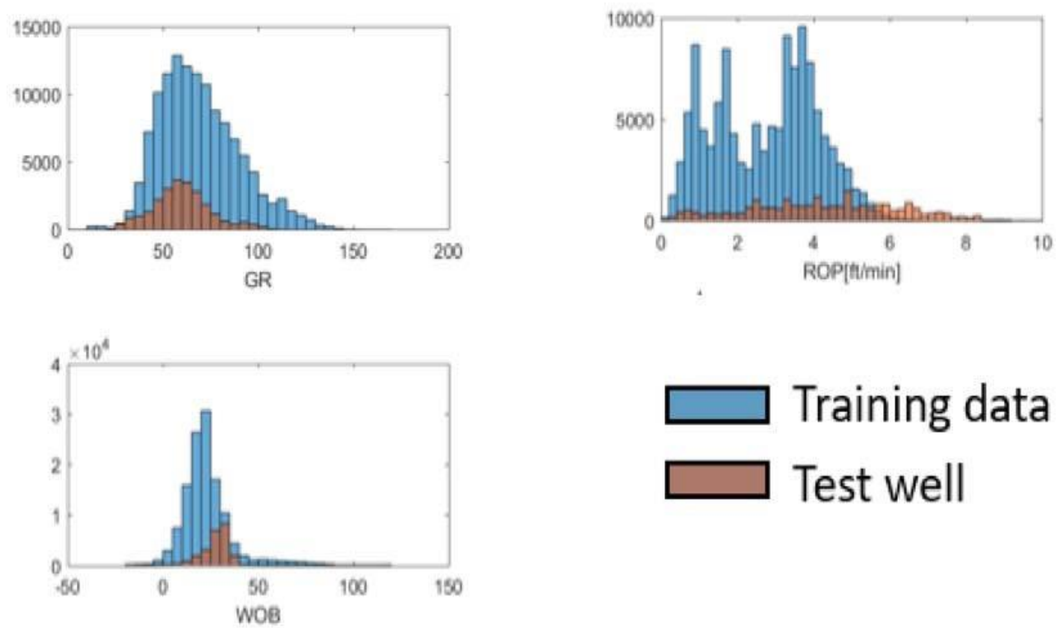

Figure 4—Example of histogram overlay to illustrate input range OOR; GR and WOB are in range, but ROP is partly OOR. The training data includes all the wells used in the model, the test well data includes the data of that single well only.

In the case where advanced log data is available for the test well, the validation follows the same steps as for the blind wells used to evaluate the training models. However, in most cases there are no measured logs available other than Gamma/Res – in these situations it is still possible to confirm confidence in the results by:

- Using several models or model variations and comparing the results to evaluate the robustness of the solution
- Quality Controlling the results by comparing with wells in training or if available with nearby offset wells
- Verifying the trends of the simulated results, both between themselves and against measured curves such as Gamma ray.

Case studies/validation of the AI logs results

In this section we present 3 case studies where the Service Company was tasked by the Operator to build models and generate AI logs based on drilling data; all cases are distinct offshore applications. For all cases, we present results on simulations of DTC and RHOB, even though models for DTS and NPHI may have been developed.

Case study I: Trinidad and Tobago East Coast Marine Area

Preamble

The first case study selected for this paper corresponds to a vertical and deviated offshore application in Trinidad and Tobago. This case study used a total of 7 wells (including a couple of mother bores and sidetrack holes) with drilling data and LWD logs provided by the Operator. The main challenge in this case is the limited number of logs and drilling data spanning common depth intervals to train the model at the time of the study (additional data is expected as the area continues to be developed).

The fields in discussion have either been producing since early 2000s or have been sufficiently appraised in the reservoir section. There is insufficient incentive to risk radioactive and sonic tools in the overburden section, and as such, the overburden section usually have only LWD GR and RES planned in the development wells. However, we believe logs particularly Density and compressional sonic in the overburden could be used in geomechanics borehole studies and real time monitoring. It would add value to the project by drilling optimization and predicting potentially difficult to drill intervals. Primary objective of applying the AI-based technique is to generate logs in the overburden to enable some of the geomechanics studies discussed above. Another potential use of the predicted logs is in the evaluation of sidetrack wells, where log data are often not acquired to save costs and minimize operational risk.

AI Log Models

As mentioned earlier, the data available for model building was scarce and a main goal of the effort was to determine if the AI method could be successfully applied in such a case. The amount of data available was not the same for all the targeted channels and in some cases the entirety of data useful for training originated from a single well. Figure 5 shows overlays of the simulated RHOB and DTC curves versus the measured petrophysical logs in the mother bore. It was not possible to directly compare simulation and measured logs in the same borehole as the sidetrack well was not logged. The overlays are shown in the portion of the hole after the split between the mother bore and the side-track. Figure 6 also shows an overlay of the GR channel for both wellbores to help in comparing the results. As shown in Fig. 6 the simulated curves are in good agreement with the measurements in the mother bore. The corresponding NRMSE numbers are 4.4% for RHOB when comparing the logs in the two holes aligned on MD. Notice that the areas with increased misfit between AI logs and measured logs correspond to areas where the rock also differs as attested by the separation in the GR curves.

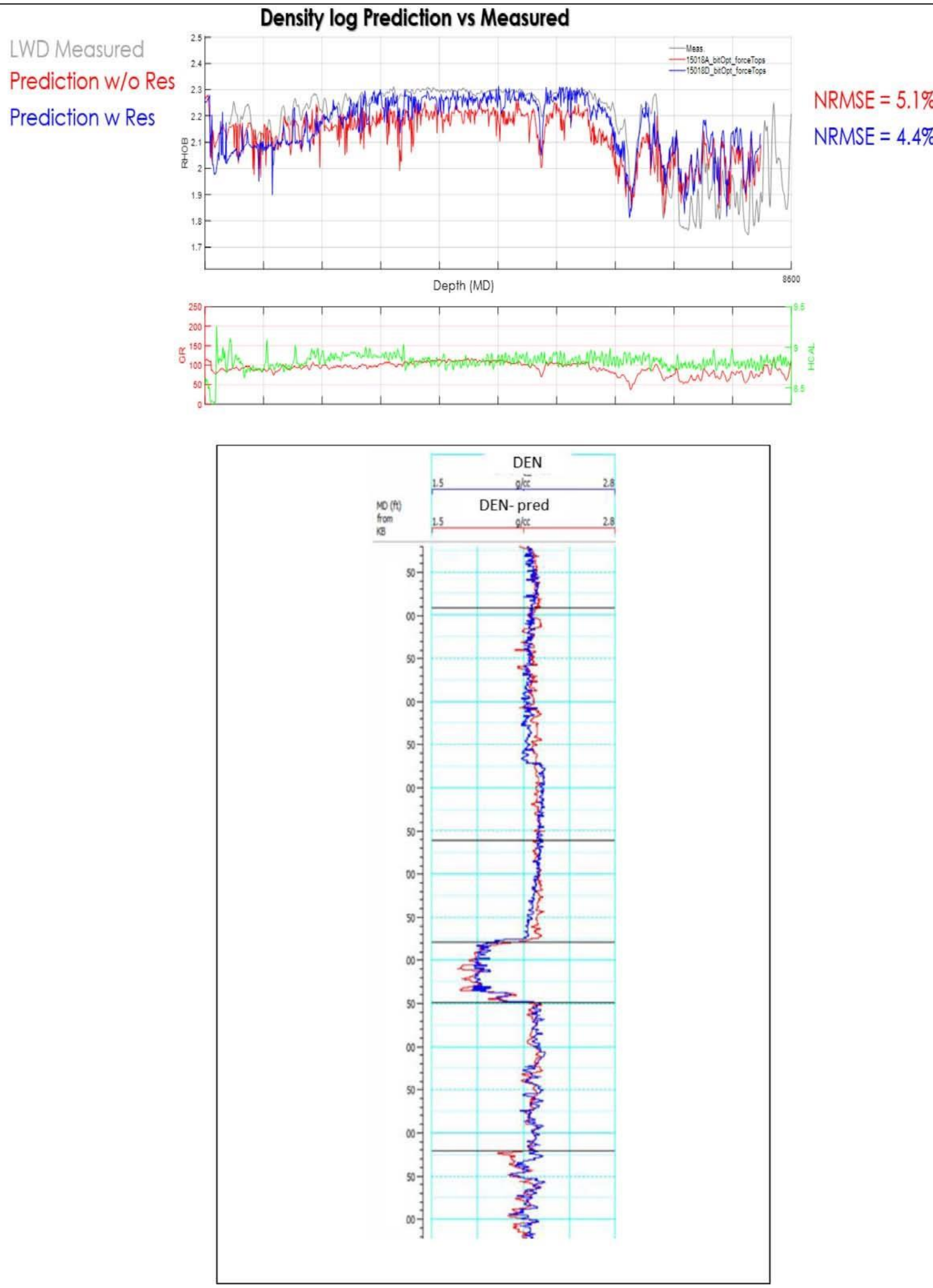

Figure 5—Figure shows the logged Density log in blue and the AI-predicted Density log in red. The statistics of the comparison of model and data are shown above.

Case study II: Offshore Gulf of Mexico (GOM1)

Preamble

The second case study is for a vertical and deviated offshore well in the Gulf of Mexico but the exact location will remain undisclosed. This case study used a total of 4 wells (2 mother bores, each with a side track hole) with drilling data and LWD logs provided by the Operator. A key goal for the operator is to utilize the AI log model in future wells to generate petrophysical logs in sections of the wellbore where advanced data cannot be acquired due to hole size limitations or to infill data gaps in the event of missing data due to tool failures or other operational issues. The Operator is also interested in utilizing the real-time AI-generated logs to aid real-time pore pressure prediction. As with the first case, data scarcity is an issue. Some areas could not be modeled with the data available at the present time. However others area could be modeled and for the sake of this paper we will focus on these results.

AI Log Models

The results shown in Figure 6 for DTC and RHOB, respectively, are based on a two-well model. In this case the overlays compare simulations and measurements in the same borehole. The simulated curves match the measurements reasonably well, with NRMSE numbers of 2.4% for RHOB and 4.8% for DTC.

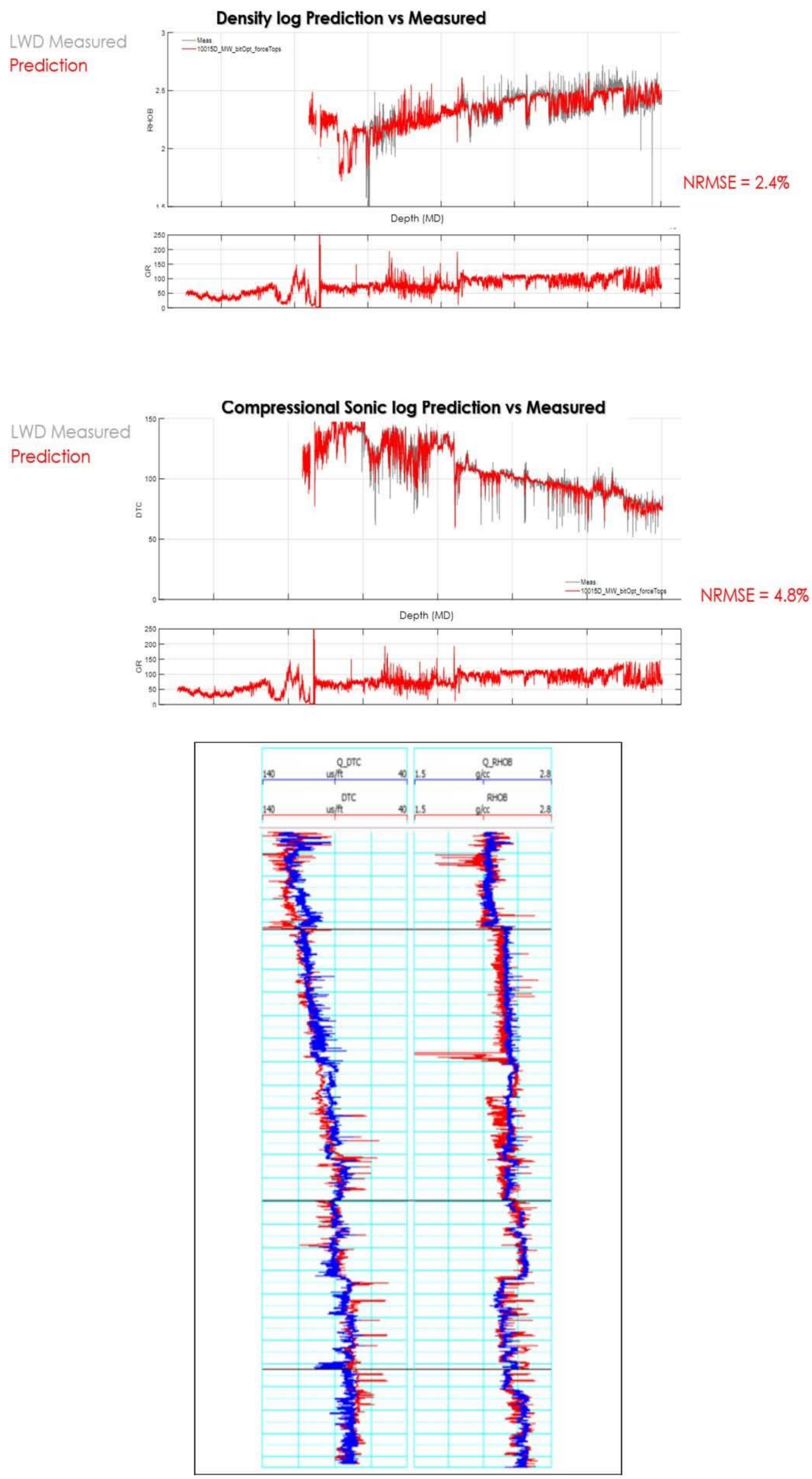

Figure 6—Figure shows the logged Sonic (L) and Density (R) logs in blue and the AI-predicted Sonic and Density logs in red. The statistics of the comparison of model and data are shown above.

Discussion

Generating AI logs from the drilling, mudlogging data and Gamma/Res logs have several advantages:

1. Increase the value of the information that is typically not utilized.
2. Provide formation evaluation logs in intervals where even the basic tools such as RHOB, NEU or DTC tools are not run
3. Real-time prediction for shallow-hole sections without formation evaluation logs
4. The integration of AI logs into the Operator's operations and software stack will be via a developed Techlog plug-in into the Operator's desktop-based log analysis software platform.
    - This Techlog plug-in leverages existing interpretative tools and WITSML capabilities available in commercially available software. Customized workflows and visualizations are standardized to allow for processes tailored to the AI model creation and model operations processes, including streamlined data conditioning, ANN model selection, and QC of input and output logs.
5. Using cloud and microservice technology to simplify technology collaboration
    - The software architecture incorporates a cloud architecture design for the backend and a lightweight user interface which plugs directly into the user's desktop software. Once the input logs and drilling data have been selected, they are packaged, encrypted and sent to the cloud for processing. Alternatively, the processing can occur on a local server.
6. Project can be managed by a Petrophysicist or a Geologist and no data transfer required with third party company
    - Running in a secure environment, the input data is decrypted and then processed by the neural network. The results are then encrypted and delivered back to the user and displayed in their desktop tool. This architecture has the advantage of centralizing the management of the available neural network models, including versioning and storing metadata on how the network was trained.

Conclusions

The results of this study indicate the ANN methodology provides synthetic logs data comparable in quality to measured conventional LWD or wireline logging tools over the study area. This required adequate calibration of offset well data and an understanding of the geological settings. Due to the inherent uncertainty and errors in AI logs, for reservoir characterization and pay calculation, measured LWD or wireline logs in offset wells are crucial for the reservoir hole section, providing calibration of the ANN model and prediction in areas of the reservoir section without data due to borehole or environmental conditions.

In summary the AI log approach provides several benefits:

- These include a framework for producing DTC, DTS, NPHI and RHOB logs in one pass from a standard set of LWD Gamma/Res, drilling and mudlogging data, which is undeniably a step-up from having no information as is generally the case in the overburden intervals.

- The next step is to use the technology to generate synthetic logs for potential applications in real-time drilling optimization, borehole stability studies and pore pressure prediction, especially for the shallow hole or overburden section monitoring.

To ensure effective operational implementation of the AI log methodology, a Techlog plug-in is being developed to aid with real-time data ingestion, processing and visualization of the AI logs – and integrate the delivery with other petrophysical analysis workflows. By leveraging cloud and microservice technology, it makes log data processing and related task collaboration much easier and allows the use of more powerful hardware in large model creation exercises and real-time model operation scenarios. The Techlog GUI plug-in into the user's desktop software allows for streamlined integration of existing software tools to QC both (i) measured logs and drilling data before usage as part of model creation, and (ii) the AI logs generated by the ANN.

Acknowledgements

The authors would like to thank Shell Trinidad & Tobago Ltd, Shell Exploration & Production Company and Quantico Energy Solutions for permission to publish this work.

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